

## ARTIFICIAL IMMUNE OPTIMIZATION: TESTS AND COMPARISON WITH EVOLUTIONARY ALGORITHM

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### ABSTRACT

#### 1. Introduction

The paper deals with an application of global optimization methods like the artificial immune system or the evolutionary algorithm to the optimization problems. The main feature of these methods is to simulate biological processes. The evolutionary methods are based on the theory of evolution. The other global optimization method is based on the mechanism discovered in biological immune systems. The main advantage of both methods is the fact that these approaches do not need any information about the gradient of the fitness function and gives a strong probability of finding the global optimum. The main drawback of the approaches is the long time of calculations.

#### 2. The artificial immune system

The artificial immune systems [1] are developed on the basis of a mechanism discovered in biological immune systems. An immune system is a complex system which contains distributed groups of specialized cells and organs. The main purpose of the immune system is to recognize and destroy pathogens - funguses, viruses, bacteria and improper functioning cells. The lymphocytes cells play a very important role in the immune system. The lymphocytes are divided into several groups of cells. There are two main groups B and T cells, both contains some subgroups (like B-T dependent or B-T independent). The B cells contain antibodies, which could neutralize pathogens and are also used to recognize pathogens. The artificial immune systems (AIS) Balthrop J. et al [5], de Castro L. N and Timmis J. [3], de Castro L. N. and Von Zuben F. J. [4] take only a few elements from the biological immune systems. The most frequently used are the mutation of the B cells, proliferation, memory cells, and recognition by using the B and T cells. The presented approach is based on the Wierzchoń S. T. (2001) algorithm [1], but the mutation operator is changed. The Gaussian mutation is used instead of the nonuniform mutation in the presented approach.

#### 3. Evolutionary algorithm

Sequential genetic and evolutionary algorithms are well known and applied in many areas of optimization problems [2].

The main aim of the evolutionary algorithm is the simulation of biological processes based on heredity (genetics) and on the natural selection (the theory of evolution) to create the optimal individuals (solutions) presented by single chromosomes.

#### 4. Example (comparison between EA and AIS)

The numerical examples present the comparison between an artificial immune system and the sequential and distributed evolutionary algorithms. The comparison is performed on the base of the optimization of the known mathematical functions, i.e.: the Branin function with 2 design variables, the Goldstein-Price function with 2 design variables, the Rastrigin function with 20 design variables, and the Griewangk function with 20 design variables (table 1), for the best parameters of the algorithms (detected earlier for these functions).

Table 1 Optimize function (Griewangk function)

<b>Griewangk function</b>											
Tested mathematical function		Comparison between AIS and EAs									
$F(x) = 1 + \sum_{i=1}^n \frac{x_i^2}{4000} - \prod_{i=1}^n \left( \cos\left(\frac{x_i}{\sqrt{i}}\right) \right), \text{ for } n=2$ $(-600 \leq x_i \leq 600), \min F(x) = F(0,0,\dots,0) = 0$		<p>Comaparision AIS with EA - Griewangk function</p> <table border="1"> <caption>Data for Comparison AIS with EA - Griewangk function</caption> <thead> <tr> <th>Method</th> <th>Average no. object fun. evaluations</th> </tr> </thead> <tbody> <tr> <td>1 - AE Sequential</td> <td>22285</td> </tr> <tr> <td>2 - AE Distributed</td> <td>13594</td> </tr> <tr> <td>3 - AIS</td> <td>6019</td> </tr> </tbody> </table>		Method	Average no. object fun. evaluations	1 - AE Sequential	22285	2 - AE Distributed	13594	3 - AIS	6019
Method	Average no. object fun. evaluations										
1 - AE Sequential	22285										
2 - AE Distributed	13594										
3 - AIS	6019										
<b>Optimal parameters -AIS</b>											
the number of memory cells	the number of the clones	crowding factor	Gaussian mutation								
2	2	0.45	0.1								
<b>Optimal parameters -EA</b>											
The number of subpopulations	The number of chromosomes in each subpopulation	The probability of simple crossover	The probability of Gaussian mutation								
1	10	100%	100%								

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